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A dynamic bi-objective model for after disaster blood supply chain network design; a robust possibilistic programming approach

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Abstract

Health service management plays a crucial role in human life. Blood related operations are considered as one of the important components of the health services. This paper presents a bi-objective mixed integer linear programming model for dynamic location-allocation of blood facilities that integrates strategic and tactical decisions. Due to the epistemic uncertain nature of strategic decisions, in order to cope with the inherent uncertainties, a robust possibilistic programming approach is applied to the proposed model. Finally, to test the applicability of the proposed model, sensitivity analysis and some numerical examples are being proposed.

Keywords. Health service management, robust possibilistic programming, blood supply chain, disaster, dynamic bi-objective model

1-Introduction and literature review

Healthcare services play a vital role when the human lives are addressed. This important issue has been received the attention of both practitioners and academia for many years and still is an interesting research avenue (Smith-Daniels et al., 1998), (Møller-Jensen and Kofie, 2001), (Oztekin et al., 2010), (Zepeda et al., 2016) and (Detti et al., 2017). Along with the other components of the health service network, blood supply chain is an important part of healthcare systems especially when addressing emergencies and disasters. Natural disasters like earthquakes and floods or even man-made disasters cannot be predicted efficiently. Eventually, any disaster will absolutely cause a sudden increase in demand of blood products. To avoid any devastating shortages in blood and its direct derivative products the national blood supply chain managers should come up with a precise, robust and effective supply-consumption plan. Reaching such narrow plan is practically impossible because most of the parameters of these systems are tainted with a high degree of uncertainty (Mousazadeh et al., 2018) and (Azadeh et al., 2017). The ultimate goal of a healthcare system is “to reduce healthcare inequalities”, to achieve this goal, designing a proper decision making system for determining the optimal location-allocation decisions for blood products is an immediate need.

Facility location problem is one of the early problems which its applications are widely used in healthcare systems.

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Location-allocation problem is a classical extension of facility location problem which locates a set of new facilities regarding minimum transportation costs and determines an optimal number of facilities to be placed in a specific area in order to satisfy the demand (Azarmand and Neishabouri, 2009).

Location-allocation problem have been investigated thoroughly in several healthcare studies, interested readers can refer to Ahmadi-Javid et al. (2017) for more details.

Blood distribution problems are categorized into three hierarchical levels; single hospitals (Heddle et al., 2009), regional blood centers (Gregor et al., 1982) and (Berzigotti and Bosch, 2016) and supply chain level (Fahimnia et al., 2017) and (Beliën and Forcé, 2012)). Some researchers have studied all these levels, while others have focused only on one level.

Generally, there are three specific time horizon for planning relief activities in case of emergencies: before, during and after a disaster. Here, we study the after disaster time interval. Remember that the post-disaster period is comparatively short and yet the most important window in saving the victims. In order to address this gap this study mainly focuses on this specific period and a short-term planning model with uncertainty considerations is proposed.

In contrast with traditional and common objectives in the business world, relief supply chains mostly focus on objectives related to human life. Cost-based objective functions usually are in conflict with service level and satisfaction degree based objectives. In this study the main objective is to be as responsive as possible in life saving and yet to be efficient at the same time.

Blood is one of the most important items in after disaster relief procedure and this paper proposes a multi-period, multi-objective optimization model with a robust possibilistic approach to handle the problem dynamics, trade-offs and uncertainties. The proposed multi-objective disaster relief logistics model is formulated as a mixed-integer, programming location-allocation model using a robust and minimax approach to obtain a more equitable, robust and reliable distribution plan of blood.

There aren't adequate studies addressing the after disaster relief programs from the perspective of blood supply chain management. Here studies on both blood supply chain management and after disaster relief programming efforts along with the studies directly addressing the after disaster relief programming in the blood supply chain are investigated. On the other hand, relevant literature on location-allocation problem in healthcare and blood supply chain network design should be investigated to point out the gap. A comprehensive survey on applications of operational research in healthcare services is presented in Rais and Viana (2011).

As the investigations on relevant literature reveals, the epistemic uncertainty of input parameters in blood supply chain problem has been underrated and there are not adequate mathematical models. Considering in real-life after disaster relief programs, all of the parameters are highly tainted with uncertainty and ambiguity. For that reason, neglecting the vague nature of input parameters may lead to a tragedy and expose the managers to high risks. To fill out this gap, a novel dynamic multi-objective mathematical programming model based on robust possibilistic programming approach is proposed for location-allocation decisions for an after disaster relief plan.

The remainder of the paper is organized as follows. Section 2 focuses on the problem definition and model assumptions, parameters and model formulations. Next is introducing the procedure in which the multi-objective model is reduced into a single objective one. Section 4 is the implementation and evaluation of the proposed model. At last, in the final section of the paper conclusions and future research directions are formulated.

2-Problem description and formulation

Here, a multi-period bi-objective model for after disaster blood supply chain management is proposed. In this problem, the donators serve as the supply points whether donating blood directly to a main blood facility known as blood storage and processing center (MBF) or to a temporary blood collecting facility (TBF). Collected blood in each TBF must be delivered to the storage and processing center for preserving and further use. A scheme of events in this chain is illustrated in figure 1. To increase the blood donators' coverage, a TBF can possibly move to another location at the end of each period.

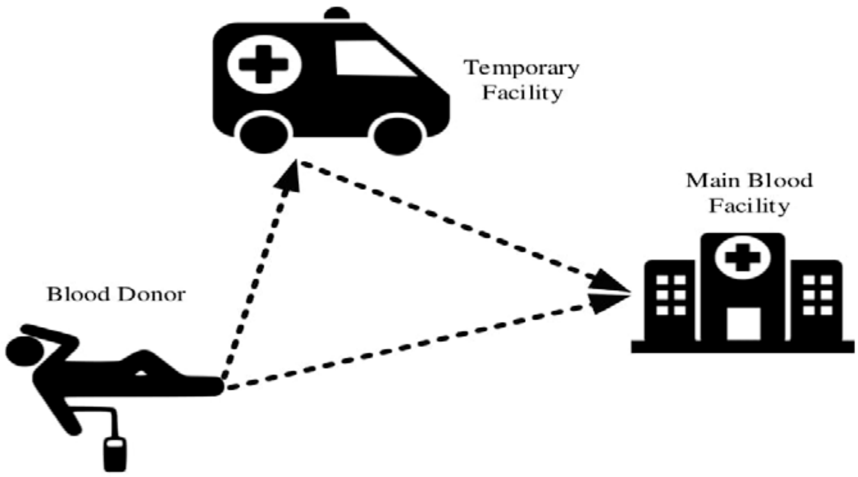

Fig 1. Scheme of the events in the under study blood supply chain

The indices, parameters and variables used to formulate the problem are as follows:

Indices

I Index of blood donator group locations (*BDG*) $i=1,\ldots,I$

J Index of temporary blood facility candidate locations (*TBF*) $j=1,\ldots,J$

N Index of main blood facility candidate locations (*MBF*) $n=1,\ldots,N$

T Index of planning time periods $t=1,\ldots,T$

Parameters

$\tilde{C}_{ij}$ Cost of transportation from BDG_i to TBF_j

$\tilde{C}_{in}$ Cost of transportation from BDG_i to MBF_n

$\tilde{C}_{jn}$ Cost of transportation from TBF_j to MBF_n

$\tilde{C}_{j_1j_2}$ Travelling cost of a *TBF* from location j_1 to location j_2

$C\tilde{a}p_j$ Collecting capacity of the j^{th} *TBF*

$C\tilde{a}p_n^s$ Storage capacity of the n^{th} *MBF*

$C\tilde{a}p_n^p$ Processing capacity of the n^{th} *MBF*

$\tilde{h}_n^t$ Inventory handling cost at n^{th} *MBF* in period *t* per unit

$\tilde{D}_n^t$ Quantity of demand in n^{th} *MBF* in period *t*

$\tilde{S}_i^t$ Quantity of possible blood supply from BDG_i in period *t*

$\tilde{A}$ Possible maximum number of *TBFs*

Variables

XT_{ij}^t Equals 1, if BDG_i is assigned to TBF_j in period *t*, 0 otherwise

XM_{in}^t Equals 1, if BDG_i is allocated to MBF_n in period *t*, 0 otherwise

$YT_{j_1j_2}^t$ Equals 1, if a *TBF* is going to move from location j_1 to location j_2 in period *t*, 0 otherwise

YM_{jn}^t Equals 1, if TBF_j is allocated to MBF_n in period *t*, 0 otherwise

QXT_{ij}^t Quantity of donated blood from BDG_i to TBF_j in period *t*, 0 otherwise

QXM_{in}^t Quantity of delivered blood from BDG_i to MBF_n in period *t*, 0 otherwise

QYM_{jn}^t Quantity of delivered blood from TBF_j to MBF_n in period *t*, 0 otherwise

I_n^t Quantity of inventory held in MBF_n in period *t*

B_n^t Quantity of shortage in MBF_n in period *t*

Using the abovementioned notations, the proposed problem can be formulated as follows.

$$MinZ_1 = \sum_{t=1}^{T} Max(B_n^t) \tag{1}$$

$$MinZ_2 = \sum_{i,j,t} \tilde{C}_{ij}.QXT_{ij}^t + \sum_{i,n,t} \tilde{C}_{in}.QXM_{in}^t + \sum_{j,n,t} \tilde{C}_{jn}.QYM_{jn}^t + \sum_{n,t} \tilde{h}_n^t.I_n^t + \sum_{j_1,j_2,t} \tilde{C}_{j_1 j_2}.YT_{j_1 j_2}^t \tag{2}$$

$$\sum_j XT_{ij}^t + \sum_n XM_{in}^t \geq 1 \qquad \forall i,t \tag{3}$$

$$\sum_n YM_{jn}^t \geq 1 \qquad \forall j,t \tag{4}$$

$$QXT_{ij}^t \leq XT_{ij}^t.M \qquad \forall i,j,t \tag{5}$$

$$QXM_{in}^t \leq XM_{in}^t.M \qquad \forall i,n,t \tag{6}$$

$$QYM_{jn}^t \leq YM_{jn}^t.M \qquad \forall j,n,t \tag{7}$$

$$\sum_j QXT_{ij}^t + \sum_n QXM_{in}^t \leq \tilde{S}_i^t \qquad \forall i,t \tag{8}$$

$$\sum_i QXT_{ij}^t \leq C\tilde{a}p_j \qquad \forall j,t \tag{9}$$

$$\sum_n QYM_{jn}^t \leq \sum_i QXT_{ij}^t \qquad \forall j,t \tag{10}$$

$$I_n^t \leq C\tilde{a}p_n^s \qquad \forall n,t \tag{11}$$

$$\sum_i QXM_{in}^t + \sum_j QYM_{jn}^t \leq C\tilde{a}p_n^p \qquad \forall n,t \tag{12}$$

$$\sum_i QXM_{in}^t + \sum_j QYM_{jn}^t + I_n^{t-1} = I_n^t \qquad \forall n,t \tag{13}$$

$$B_n^t = D_n^t - \left(\sum_i QXM_{in}^t + \sum_j QYM_{jn}^t \right) \qquad \forall n,t \tag{14}$$

$$\sum_{j_1} YT_{j_1 j_2}^t \leq 1 \qquad \forall j_2,t \tag{15}$$

$$\sum_{j_2} YT_{j_1 j_2}^t \leq YT_{j,j_1}^{t-1} \qquad \forall j_1,t \tag{16}$$

$$\sum_{j_1,j_2} YT_{j_1 j_2}^t \leq \tilde{A} \qquad \forall t \tag{17}$$

$$XT_{ij}^t \leq \sum_{j_1} YT_{j_1 j}^t \leq 1 \qquad \forall i,j,t \tag{18}$$

$$XT_{ij}^t, XM_{in}^t, YT_{j_1 j_2}^t, YM_{jn}^t \in \{0,1\} \qquad QXT_{ij}^t, QXM_{in}^t, QYM_{jn}^t, I_n^t \geq 0 \ \& \ integer \tag{19}$$

The first objective function represented in equation (1) minimizes the maximum amount of shortage in demand points. As in this problem any shortage may lead to loss of lives (not profit), the min-max approach is much better than min-sum approach. We will linearized this objective later. Second objective function represented in equation(2), minimizes the summation of attributed costs, including transportation costs and blood process and holding costs. It is clear that these two objective functions are opposing each other.

Constraints (3) ensure that each blood donating group is covered by at least one temporary blood facility or one main blood facility in each period. Constraints (4) indicate that each temporary blood facility is assigned to a main blood facility. Constraints (5)-(7) ensure that there is a material flow as long as an entity is assigned to an upper echelon entity. Constraints (8) indicate the supply limitations in blood donating groups. Constraints (9) indicate the capacity limitations on temporary blood facilities. Constraints (10) indicate the limitations on delivered bold quantities to the main facilities. Constraints (11) and (12) indicate the capacity limitations in main blood facilities. Constraints (13) indicate the material flow balance in main blood facilities in each period. Constraints (14) indicate the shortage and unsatisfied demand amounts in each period. Constraints (15)-(18) ensure that the temporary blood facilities assignments and movements follow a feasible sequence in each period. Constraints (19) are the non-negativity and binary restrictions of variables.

As already mentioned, first objective function is a nonlinear equation which could easily be changed to a linear equation as following:

$$
\begin{aligned}
&MinZ_1 = \sum_t MaxShortage_t \\
&MaxShortage_t \geq B_n^t \qquad \forall n,t \\
&MaxShortage_t \geq 0 \qquad \forall t
\end{aligned} \tag{20}
$$

Where (MaxShortage$_t$) stands for the possible maximum value of the B_k^t.

2-1-Accounting for data uncertainty

Parameters of after disaster planning models are tainted with a huge degree of uncertainty. Modeling and investigating these problems without uncertainty considerations will not lead to a practical approach to be used in after disaster relief programs. Furthermore, as this problem deals with human life robustness of the solutions is in high regard in comparison with profit based problems. In order to deal with the uncertain nature of the problem, a robust possibilistic programming approach based on *Me* measure is applied to the proposed model. Me measure is one the most recent fuzzy measures in the literature.

2-2-Fuzzy mathematical programming approach

Fuzzy mathematical programming approach is one the frequently used programming approaches when addressing uncertainty along with flexible goals and elastic constraints. Possibilistic chance-constraint programming (PCCP) approach is one of the wide spread methods in the literature because of its ability on controlling the confidence level of constraints and its compatibility with different types of fuzzy numbers (Pishvaee et al., 2012a). Necessity (N) and Possibility (π) measures are representing the extreme attitude of the parameters. However, CCP models based on Credibility (Cr) measure are proven to be more effective (Pishvaee et al., 2012b). Given a trapezoidal fuzzy number, $\xi=(d_1,d_2,d_3,d_4)$where $d_1<d_2<d_3<d_4$.

While credibility measure is more flexible than two extreme optimistic and pessimistic measures, this approach provides DMs with a single moderate point between necessity and possibility. Xu and Zhou (Xu and Zhou,, 2013) developed a new fuzzy measure (Me measure) to provide a spectrum of decisions instead of a single moderate point. In equation(21), λ ($0 \leq \lambda \leq 1$) is the tuning parameter which states the optimistic or pessimistic attitude of the DM.

$$
Me\left(\tilde{\xi}\right) = \lambda\pi\left(\tilde{\xi}\right) + \left(1-\lambda\right)N\left(\tilde{\xi}\right) \tag{21}
$$

$$
Me\left(\tilde{\xi} \leq r\right) = \begin{cases} 0 & r \leq d_1 \\ \lambda \dfrac{r-d_1}{d_2-d_1} & d_1 \leq r \leq d_2 \\ \lambda & d_2 \leq r \leq d_3 \\ \lambda + (1-\lambda)\dfrac{r-d_3}{d_4-d_3} & d_3 \leq r \leq d_4 \\ 1 & r \geq d_4 \end{cases}, Me\left(\tilde{\xi} \geq r\right) = \begin{cases} 1 & r \leq d_1 \\ \lambda + (1-\lambda)\dfrac{d_2-r}{d_2-d_1} & d_1 \leq r \leq d_2 \\ \lambda & d_2 \leq r \leq d_3 \\ \lambda \dfrac{d_4-r}{d_4-d_3} & d_3 \leq r \leq d_4 \\ 0 & r \geq d_4 \end{cases} \tag{22}
$$

And if $\tilde{\xi} \geq 0$, based on equation(22), expected value using *Me* measure is calculated as follows:

$$
E^{Me}\left[\tilde{\xi}\right] = \int_0^{+\infty} Me\left(\tilde{\xi} \geq r\right)dx - \int_{-\infty}^{0} Me\left(\tilde{\xi} \leq r\right)dx = \frac{1-\lambda}{2}(d_1+d_2) + \frac{\lambda}{2}(d_3+d_4) \tag{23}
$$

The crisp counterparts of both $Me\left(\tilde{\xi} \geq r\right) \geq \alpha$ and $Me\left(\tilde{\xi} \leq r\right) \geq \alpha$ would be as follows:

$$Me\left(\tilde{\xi}\le r\right)\ge\alpha\Leftrightarrow\begin{cases} if\quad \lambda<0.5\Rightarrow\lambda+(1-\lambda)\dfrac{r-d_3}{d_4-d_3}\ge\alpha\Rightarrow r\ge\dfrac{(\alpha-\lambda)d_4+(1-\alpha)d_3}{1-\lambda} \\ if\quad \lambda\ge0.5\Rightarrow\begin{cases}\lambda\dfrac{r-d_1}{d_2-d_1}\ge\alpha\Leftrightarrow r\ge\dfrac{(\lambda-\alpha)d_1+\alpha d_2}{\lambda} & d_1\le r\le d_2 \\ \lambda & d_2\le r\le d_3 \\ \lambda+(1-\lambda)\dfrac{r-d_3}{d_4-d_3}\ge\alpha\Leftrightarrow r\ge\dfrac{(\alpha-\lambda)d_4+(1-\alpha)d_3}{1-\lambda} & d_3\le r\le d_4\end{cases}\end{cases}\tag{24}$$

$$Me\left(\tilde{\xi}\ge r\right)\ge\alpha\Leftrightarrow\begin{cases} if\quad \lambda<0.5\Rightarrow\lambda+(1-\lambda)\dfrac{d_2-r}{d_2-d_1}\ge\alpha\Rightarrow r\le\dfrac{(\alpha-\lambda)d_1+(1-\alpha)d_2}{1-\lambda} \\ if\quad \lambda\ge0.5\Rightarrow\begin{cases}\lambda+(1-\lambda)\dfrac{d_2-r}{d_2-d_1}\ge\alpha\Leftrightarrow r\le\dfrac{(\alpha-\lambda)d_1+(1-\alpha)d_2}{1-\lambda} & d_1\le r\le d_2 \\ \lambda & d_2\le r\le d_3 \\ \lambda\dfrac{d_4-r}{d_4-d_3}\ge\alpha\Leftrightarrow r\le\dfrac{\alpha d_3+(\lambda-\alpha)d_4}{\lambda} & d_3\le r\le d_4\end{cases}\end{cases}\tag{25}$$

In healthcare problems where they are highly sensitive to the uncertain parameters the main goal of managers is to satisfy the possibilistic chance constraints with a fairly high chance. So in these problems managers tend to develop a pessimistic approach rather than an optimistic one. In other words, the λ parameter would take a value less than 0.5.

To work more convenient we develop the compact form of the proposed model as follows:

$$\begin{aligned} &Min\ Z_1=X \\ &Min\ Z_2=TY+WX \\ &X,Y\in G(x,y) \\ &Y\in\{0,1\}\quad X\ge 0\ \&\ integer \end{aligned}\tag{26}$$

Now without losing any generality, assume that T and W vectors are representing the imprecise and fuzzy parameters of the model. Expected value operator is used to convert the objective functions to their crisp equivalent and *Me* measure is adopted to deal with constraints contain vague parameters. The parameters are assumed to follow a trapezoidal possibility distribution, $\tilde{\xi}=(\xi_1,\xi_2,\xi_3,\xi_4)$. With these descriptions the (26) model can be reformulated as follows:

$$\begin{aligned} &Min\ Z_1=X \\ &Min\ E[Z_2]=E\left[\tilde{T}\right]Y+E\left[\tilde{W}\right]X \\ &Me\left\{LX\ge\tilde{D}\right\}\ge\alpha \\ &Me\left\{MY\le\tilde{K}\right\}\ge\beta \\ &X,Y\in F(x,y) \\ &Y\in\{0,1\}\quad X\ge 0\ \&\ integer \end{aligned}\tag{27}$$

By applying transformations discussed in equations (23) through(25), the crisp equivalent of the model (27) is as follows:

$$
\begin{gathered}
Min\ Z_1 = X \\
Min\ E[Z_2] = \left[\frac{1-\lambda}{2}(T_1+T_2)+\frac{\lambda}{2}(T_3+T_4)\right]Y+\left[\frac{1-\lambda}{2}(W_1+W_2)+\frac{\lambda}{2}(W_3+W_4)\right]X \\
LX \geq \frac{(\alpha-\lambda)D_4+(1-\alpha)D_3}{1-\lambda} \\
MY \leq \frac{(\beta-\lambda)K_1+(1-\beta)K_2}{1-\lambda} \\
X, Y \in F(x,y) \\
Y \in \{0,1\} \quad X \geq 0\ \&\ integer
\end{gathered} \tag{28}
$$

While the (28) model deals with data ambiguity, it fails to track the objective function value's deviation from the expected value. These deviations cost a lot especially in healthcare systems where any lost means human life. Secondly, in this approach the minimum confidence level of constraints are determined based on decision maker's preferences which won't necessarily lead into optimality. To fill out these shortcomings, a combination of robust programming and fuzzy programming approaches are introduced (Zahiri et al., 2014).

A robust solution has feasibility robustness along with optimality robustness (Pishvaee et al., 2012a). A solution is feasibly robust only if it remains feasible for all realizations of imprecise parameters and it is optimally robust if it the equivalent objective function value remains (near) optimal for all realizations of uncertain parameters. In classical robust possibilistic programming approach the Necessity measure is applied to deal with vague and imprecise data but as already discussed, *Me* measure provides a more realistic perspective of the problem for the decision makers. The *Me*-based robust possibilistic programming model is developed as follows:

$$
\begin{gathered}
Min\ Z_1^{crisp} = E[Z_1]+\sigma\left(D_4-\frac{(\alpha-\lambda)D_4+(1-\alpha)D_3}{1-\lambda}\right)+\delta\left(\frac{(\beta-\lambda)K_1+(1-\beta)K_2}{1-\lambda}-K_1\right) \\
Min\ Z_2^{crisp} = E[Z_2]+\psi\left(Z_2^{Max}-E[Z_2]\right)+\sigma'\left(D_4-\frac{(\alpha-\lambda)D_4+(1-\alpha)D_3}{1-\lambda}\right)+\delta'\left(\frac{(\beta-\lambda)K_1+(1-\beta)K_2}{1-\lambda}-K_1\right) \\
LX \geq \frac{(\alpha-\lambda)D_4+(1-\alpha)D_3}{1-\lambda} \\
MY \leq \frac{(\beta-\lambda)K_1+(1-\beta)K_2}{1-\lambda} \\
X, Y \in F(x,y) \\
Y \in \{0,1\} \quad X \geq 0\ \&\ integer,\ 0.5 \leq \alpha, \beta \leq 1
\end{gathered} \tag{29}
$$

In model(29), the first term in both objective functions are the expected values of objective functions. For the second objective function the second term is minimizing the deviations of upper bound of objective function values from the expected values to control the optimality robustness of the solutions. The parameters ψ and ω are the preference weight parameters of the optimality robustness over the feasibility robustness. The last two terms of second objective function are controlling the feasibility robustness of the solutions. These terms minimize the violations of RHS of the chance constraints from their worst realized value of the uncertain parameters with penalty parameters $\delta, \sigma, \delta', \sigma'$. Interesting fact about these penalty values is that they can be interpreted due to the problem context, for instance, shortage costs can easily be redefined into these parameters. The upper bound of the second and third objective functions are calculated as follows:

$$
Z_2^{\max} = T_4 Y + W_4 X \tag{30}
$$

3-Coping with objective functions

In the literature of multi objective optimization problems there are three main approaches to tackle with multi objective function problem; priori, interactive and posteriori classes (Deb, 2014). Interactive class of approaches accumulates the favorable features of the other two approaches while preventing the inefficiencies of them. In contrast with the priori approaches, interactive methods look into the preferences of the DMs and generate Pareto-optimal solutions. In this study the interactive method proposed by Torabi and Hassini (2008), (TH) is applied to the proposed model. TH method is one of the most wide spread interactive approaches in coping with multi objective models. Interested readers may refer to (Lalmazloumian et al., 2016), (Farrokh et al., 2018), (Alavidoost et al., 2016), (Tofighi et al., 2016), (Mirmohseni et al., 2017) and (Mohammed and Wang, 2017).

The steps of the TH approach are as follows:

- ✓ Calculate the positive/negative ideal solution (PIS & NIS) for each objective function
- ✓ Determine the following linear fuzzy membership function for each objective function:

$$\mu_{Z_j}(x) = \begin{cases} 1 & Z_j(x) < Z_j^{PIS} \\ \dfrac{Z_j^{NIS} - Z_j(x)}{Z_j^{NIS} - Z_j^{PIS}} & Z_j^{PIS} \le Z_j(x) \le Z_j^{NIS} \\ 0 & Z_j(x) > Z_j^{NIS} \end{cases} \tag{31}$$

- ✓ Convert the crisp multi-objective model into a single-objective model as follows:
- ✓

$$\begin{aligned} & Max \quad \phi\tau_0 + (1-\phi)\sum_k w_k \mu_k(x) \\ & \mu_k(x) \ge \tau_0; \quad \forall k \\ & x \in F_x \ and \ \tau_0 \in [0,1] \end{aligned} \tag{32}$$

Where $\tau_0$indicate the minimum satisfaction degree of objective functions, ϕ and w_k stand for the coefficient of compromise between objective functions and importance of the j^{th} objective function.

- ✓ Determine the values of importance weight of the objective functions and coefficient of compromise between objective functions and solve the single-objective model.

4-Implementation and evaluations

In this section the validation and performance of the proposed model solution approach is investigated by two test problems. All the proposed models are coded in GAMS 24.7.4 optimization software using CPLEX solver and all the executions are implemented on a Corei7 2.40 GHz laptop with 8 GB of RAM. Note that the triangular fuzzy numbers of given uncertain parameters are considered as $(0.9\varphi, \varphi, 1.1\varphi)$. Problems size is 3*6*1*3 and 10*25*5*5 and input parameters follow a uniform distribution. The parameter values for test problems are given in table 1.

Table 1. The numerical values of the parameters in the test problems

Parameter	*Range*	*Parameter*	*Range*
$\tilde{c}_{ij}$	$\sim uniform(55,75)$	$C\tilde{a}p_n^p$	$\sim uniform(1000,1500)$
$\tilde{c}_{in}$	$\sim uniform(110,140)$	$\tilde{h}_n^t$	$\sim uniform(50,150)$
$\tilde{c}_{jn}$	$\sim uniform(30,45)$	$\tilde{D}_n^t$	$\sim uniform(250,350)$
$\tilde{c}_{j_1j_2}$	$\sim uniform(100,120)$	$\tilde{S}_i^t$	$\sim uniform(800,900)$
$C\tilde{a}p_j$	$\sim uniform(100,120)$	$\tilde{A}$	*10*
$C\tilde{a}p_n^s$	$\sim uniform(1500,2500)$		

The optimal solutions for test problems are presented in table 2. In these test problems the weight factor for the first objective function is always higher than the second one, as the shortage amounts in proposed model may lead to human casualties. As the weight factor for the first (second) objective function increases the optimal value of the corresponding objective decreases (increase). The τ_0 is the minimum satisfaction degree of the objective functions and as it's higher when the DM has a moderate attitude toward the problem. The most maximum value of TH objective function is obtained when there is a reasonable balance among objective functions satisfaction degrees. Note that the values of Z1and Z2 are calculated based on model (29).

Table 2. Results of test problems under proposed model (ϕ=0.1)

Weight factors	Test problem	MaxShortaget	Z_1^{crisp}	Z_2^{crisp}	τ_0	$\mu_{Z_j}(x)$	TH value
(0.5,0.5)	1	(8,13,7)	3910	209736	0.88	(0.91,0.88)	0.848
	2	(43,27,19,33,20)	15271	709203	0.84	(0.89,0.84)	0.838
(0.6,0.4)	1	(7,13,6)	3862	213640	0.83	(0.93,0.83)	0.864
	2	(32,23,17,23,18)	14610	712939	0.80	(0.90,0.8)	0.850
(0.7,0.3)	1	(6,10,5)	3717	221406	0.79	(0.95,0.79)	0.888
	2	(27,20,15,16,9)	14052	730081	0.78	(0.94,0.78)	0.877
(0.8,0.2)	1	(6,10,2)	3694	229687	0.77	(0.99,0.77)	0.924
	2	(17,16,8,10,5)	13503	741507	0.76	(0.95,0.76)	0.895
(0.9,0.1)	1	(5,7,0)	3604	240037	0.75	(0.99,0.75)	0.938
	2	(13,12,4,3,2)	13122	756320	0.73	(0.95,0.73)	0.906

Figure 2 depicts the conflicts of objective functions, Z1 V.s. Z2, for normalized objective function values of both test problems presented in table 2. As expected, as the values of first objective decrease the values of the second objective function increase in both test problems. DMs can choose any pair of solutions based on their preferences. The parameter ϕ in TH approach plays a balancing role between objective functions minimum satisfaction degrees and summation of objective function satisfaction degrees. For small amounts of ϕ the importance of high weighted objective function is highlighted while for large values of ϕ the minimum satisfaction degree is given more importance in model(32). Figure 3 runs the gamut from 0.1 to 1 for the parameter ϕ. The weight factor for first objective function is high as it is the first priority in after disaster relief programs and that's why first objective function values are more sensitive to the fluctuations of ϕ.

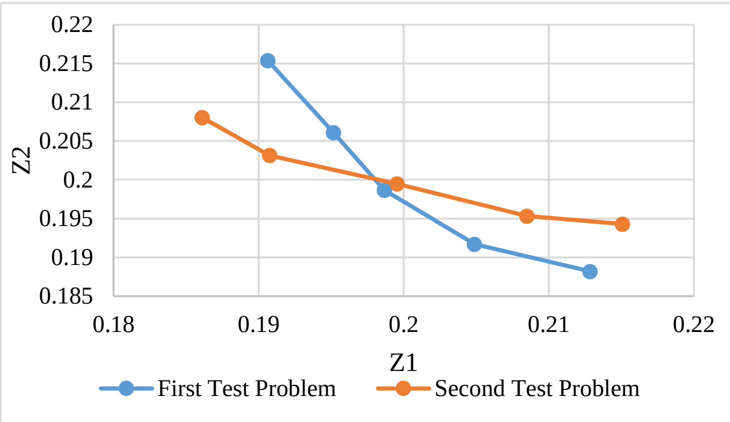

Fig 2.Normalized Pareto solutions for both test problems

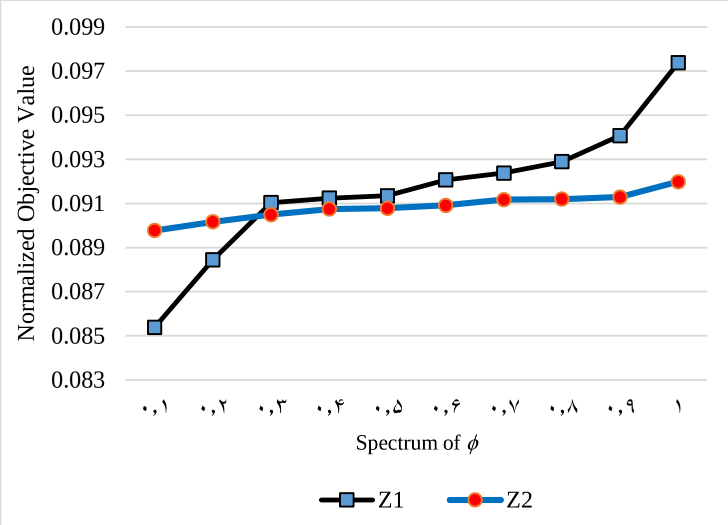

Fig 3. Normalized optimal objective function values for a spectrum of ϕ in TH approach (Test problem 1)

Finally, the behavior of the proposed model under different controlling parameters is studied. Maximum shortage amounts, objective functions values, objective function satisfaction degrees and TH objective function values are reported in table 3. Maximum shortage quantities are dependent on the values of ϕ in(32), in higher values of ϕ their values are like an upper bound for them in the lower values of ϕ. The parameters ω and ψ are indicating the penalty of violations in objective functions. For various values of these controlling parameter the general behavior of the proposed model is the same. The minimum value of λ in which the model is feasible is 0.5 and for a higher values the optimal solutions of the model in λ=0.8 is investigated. The constraints violations controlling parameters are considered to be equal to 0.6 which is indicating the relative importance of limitations on right hand side values of constraints

Table 3. Optimal solutions for second test problem, w (0.9, 0.1) and A=10

$\sigma, \sigma', \delta, \delta'$	ω	ψ	λ	ϕ	Max Shortage	Z1	Z2	$\mu_{z_i}(x)$	TH value
0.6	50	100	0.5	0.2	0	13566	538111	(1,0.79)	0.849
				0.8	0	13566	536021	(1,0.8)	0.836
			0.8	0.2	0	13701	405289	(1,0.79)	0.940
				0.8	(18,33,22,14,17)	14182	399058	(0.89,0.79)	0.832
		200	0.5	0.2	0	14566	1020071	(1,0.8)	0.922
				0.8	0	14566	1045082	(1,0.78)	0.832
			0.8	0.2	0	14566	785637	(1,0.78)	0.830
				0.8	(19,30,41,15,7)	15927	735272	(0.91,0.79)	0.803
	150	100	0.5	0.2	0	14566	608291	(1,0.77)	0.873
				0.8	(0,0,4,0)	14570	536021	(0.99,0.8)	0.947
			0.8	0.2	0	14566	396635	(1,0.79)	0.943
				0.8	0	14746	391668	(1,0.8)	0.901
		200	0.5	0.2	0	14566	1206740	(1,0.76)	0.935
				0.8	(0,0,12,5,0)	14583	1023263	(0.98,0.79)	0.876
			0.8	0.2	0	14566	840692	(1,0.76)	0.907
				0.8	0	14566	748123	(1,0.79)	0.903
	300	100	0.5	0.2	0	15566	540113	(1,0.79)	0.904
				0.8	(0,20,27,0,0)	15613	536032	(0.97,0.8)	0.891
			0.8	0.2	(0,1,0,4,4)	15907	392073	(0.99,0.8)	0.963
				0.8	(17,18,19,20,15)	15677	392490	(0.91,0.8)	0.875
		200	0.5	0.2	(0,0,26,0,0)	15592	1023578	(0.96,0.79)	0.942
				0.8	(0,12,26,0,0)	15604	1020071	(0.94,0.8)	0.931
			0.8	0.2	(0,1,0,4,0)	15907	730453	(0.99,0.8)	0.938
				0.8	(17,18,19,10,0)	15961	731486	(0.91,0.8)	0.862

5-Conclusion

Health service management plays a profound role in human life. Blood service operations are considered as the key components of health service systems. The real-life problems are mostly considered as problems with highly uncertainty in their parameter values; disasters on the other hand, propagate these uncertainties. For dealing with epistemic uncertainty in input parameters of these problems, input parameters are assumed to follow a trapezoidal fuzzy number distribution and a robust possibilistic programming approach is applied to solve the proposed model. Proposed model is a dynamic, multi-objective location-allocation mathematical model for designing a blood supply chain for after disaster relief programs. The proposed model is consisted from three distinguishable set of nodes; blood donors, temporary blood collection facilities and processing and storage centers. Two objective functions are developed, including minimizing the maximum possible shortage and minimizing the total costs. To cope with the objective functions the Torabi-Hassini approach is applied. A set of Pareto optimal solutions is calculated to provide the managers with a wide range of possible solutions. Sensitivity analysis on the trade-off coefficient between objective functions and controlling parameters are provided. The proposed model proves to be useful especially in short-term after disaster relief programs.

Developing long-term planning programs and considering the perishability of blood products are possible direction for future research. Another direction can be extending the proposed model to tackle with blood SC management as an integrated planning period for before, during and after disaster.

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